

The Economic Evaluation of Optimal Water Allocation Using Artificial Neural Network (Case Study: Moghan Plain)

Ali Sardar Shahraki¹, Somayeh Emami*²

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Abstract

Precipitation shortage, the consequent loss of several water resources, and population growth are the most critical problems in arid and semi-arid regions like Iran. Providing essential tools for optimal water resources management is considered one of the leading solutions to this problem. Since the agricultural sector is the primary user of water resources, the present study presented a model based on an artificial neural network method for the optimal allocation of water resources in the agricultural sector during the statistical period of 2007-2016. The objective function was determined for each product in the agricultural sector, product performance, product revenues, and cultivated area of the demand function. Maximizing the objective function (to maximize economic profits) and optimal allocation of water resources were; then conducted using the neural network. The results of applying the artificial neural network method to the problem of optimal water allocation showed that, in this section, higher revenues could be obtained through economic policies and changing the pattern of cultivation. Furthermore, the results revealed that about 44 percent of the optimal allocation revenues of water resources (\$115 billion) were improved between the agricultural sectors, compared to the current situation, by applying a coefficient of 0.9 compared to two coefficients of 0.75.

Keywords: Water Optimal Allocation, Artificial Neural Network, Economic, Agriculture, Moghan Plain.

JEL Classification: Q10, N5.

1. Introduction

The ever-increasing population growth and industrialization are imposing constant pressure on water resources and it is more likely

1. Department of Agricultural Economics, Faculty of Management and Economics, University of Sistan and Baluchestan, Zahedan, Iran (a.s.shahraki@eco.usb.ac.ir).

2. Department of Water Engineering, Faculty of Agriculture, Tabriz, Iran (Corresponding Author: somayehemami70@tabrizu.ac.ir).

that the available water resources may not be able to meet the future water demands. The shortage of water resources has become more severe due to the uneven distribution of available water resources among various water demand sectors and is a major constraint to economic development in many countries around the world (Ahmad et al., 2018; Sardar Shahraki et al., 2018).

Water is considered as the main limiting factor for economic development in arid and semi-arid regions like Iran. Therefore, establishing a balance between the supply and demand of water is assumed to be the most important issue in water management (Sardar Shahraki et al., 2016). Since water is not traded in the market, and most cases, it is offered to the agricultural sector at a low cost, the amount of water supply is always limited. It is, therefore, necessary to plan the optimal use of water resources (Kish Agriculture, 2002). In recent years, despite significant investments in the water sector, an increase in the water extraction cost per cubic meter from new water resources in the country, the unplanned withdrawal of some water resources, the failure to observe the principles of maintenance, the growth of the industrial sector, and urban development have led to the failure in meeting the growing demand for water in some regions so that water becomes a competitive commodity for various uses.

The targeted management and water resources allocation systems are the most fundamental issues for policymakers. Water allocation should be economically viable in ideal conditions. That is, the distribution of water tends to maximize economic profits, allocating social justice in distribution to maintain the resources, and fairly allocating water to economically weak groups. An appropriate water allocation system is, therefore, needed where water is considered a social and economic commodity. In the economic and macroeconomic programs of different countries, an increase in water resource utilization has been attributed as one of the most important indicators in agricultural development (Parhizkari et al., 2015; Sardar Shahraki et al., 2016). It has been shown that time series models, optimization algorithms, correlation, artificial neural networks, and other modern methods are highly efficient allocating and optimizing water resources.

Zerat Kish (2016) determined the price of agricultural water in the

Lishter area while estimating the optimal model of cultivation, the environmental goals, and objectives of the farmers, including an increased gross rate of return (revenue) and the desired risk. The data used included the production pattern, the use of inputs, and the prices of each input, which was selected randomly by selected utilities. The economic values of water were estimated at 250, 1500, and 3050 IRR.

Gheydari and Maroofi (2002) optimized water resource allocation using a multi-objective bargaining approach and fuzzy planning aimed at maximizing the total economic profits of water resources. They reported that it could be achieved 553636 to 496216 thousand dollars a year by reducing economic expectations (13).

Habibi Davijani et al. (2013) presented an optimization model for water resource allocation among agriculture, industry, and services sectors using the GAPSO advanced algorithm. They maximized the objective function and optimal allocation of water resources between agriculture and industry sectors by using the combined genetic-collective intelligence algorithm (GAPSO). The results showed that the cultivation pattern, the elimination of the cropping level of some products, and the use of more water resources could increase the proceeds to as high as \$114 billion in the industrial basin.

Reka et al. (2001) and Bilsa and Duarte (2001) have developed an economic optimization model for planning water resources in irrigated lands as well as an economic model for allocating water into two irrigation and hydropower sections aimed at maximizing the economic profit in northeastern Spain, respectively.

Divakar et al. (2011) proposed a model for the Chao Phraya River Basin of Thailand to maximize the net income for optimal water allocation limited to four sectors: agriculture, home, industry, and hydropower. The model is capable of improving economic profit in comparison with water allocation methods.

Babol et al. (2005) developed an integrated water resource allocation model with three models of reservoir performance, economic analysis, and water allocation along with maximizing satisfaction as well as economic net profits in the Chonburi district of East Thailand.

Salazar et al. (2007), provided peer-to-peer solutions to balance the economic profits of agricultural production by environmentally destructive impacts.

Sing and Panda (2012), used the underground water and canals, irrigation requirements of plants as well as hydrological and economic factors including the revenue and cost of producing nine plants in the cultivation pattern for the optimal water and land allocation model in India. The results revealed that the decrease in rice, mustard, barley and chickpea acreages and, in contrast, an increase in cotton, sugarcane, millet, wheat and sorghum acreages would increase the annual net profit by as high as about 26%.

Ghaffari Moghadam et al. (2012), allocated optimal water resources of Chahnimeh reservoirs using game theory models over one year. According to the estimation of the low-maximum lexicographic model of water deficit ratio, the satisfaction ratio of drinking water varied from 0.89 to 1, which were estimated at 41-0.49 and less than 1 for the agricultural sector and reservoirs' water allocation, respectively.

Dedi Liu et al. (2014) proposed a second-generation non-dominated sorting genetic algorithm to maximize the economic benefits, minimize water shortages, and maximize water load. The data were collected from Northwest Pearl River Delta in China for optimal allocation of water quantity and waste load. To simulate dynamic water flow for the water quantity allocation, Saint-Venant equations were used, and to simulate water quality for the waste load allocation, one-dimensional advection-dispersion mass transport equation was used.

Sara Kutty and Hanumanthappa (2017), used data mining techniques method to optimize water allocation. This survey paper elaborated on the theoretical background of data mining models and highlighted the applications in knowledge data discovery from a water resources database, particularly on optimal water allocation. Application of data-mining to water management is at a developmental stage and has been subjected to very few research works.

Ahmad et al. (2018), used a linear bi-level multi-objective program for optimal allocation of water resources. The bi-level model developed in this study was applied to the Swat River basin in Pakistan for the optimal allocation of water resources among competing water demand sectors and different scenarios were

developed. The application of the model showed that the SICCON was a simple, applicable, and feasible approach to solve the BLMOLP problem. Finally, the comparisons of the model results showed that the optimization model was practical and efficient when it was applied to different conditions with priorities assigned to various water users.

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According to the research, the agricultural sector has the largest share of water resources consumption. Therefore, in this research, the nonlinear purpose function, based on the amount of water consumed in the agricultural sector, was formed as the most important user of water resources. Also, in this section, limitations, and constraints were considered. Given that the objective function and other constraints followed the nonlinear process, therefore, in solving this problem, a powerful neural network method (ANN) was used to improve the economic situation by maximizing net profit for water optimal and water resource allocation.

2. Materials and Methods

2.1 The Study Area

The Moghan plain is a large area located in the north of Ardebil province and the west of the Caspian Sea between the longitudes of 47.5° and 48° E. and the latitudes of 39.20° and 39.42° N. This plain is divided into two parts by the borderline of Iran and the Republic of Azerbaijan. The part, which is called Moghan plain, is estimated to be 300-350 thousand hectares where the project of developing the exploitation of the Aras river water resources has been implemented at a level of 90 thousand hectares. The Moghan plain is located on the right bank of the Aras River, which is limited to the Aras river and Dasht-e-Mil in the Republic of Azerbaijan from the north, and along the borderline to the Republic of Azerbaijan from the east, to the city

of Germe and Meshghin Shahr from the south, and the slopes of Sabalan and is limited to the city of Ahar from the west. The location of the study site is shown in Figure 1.

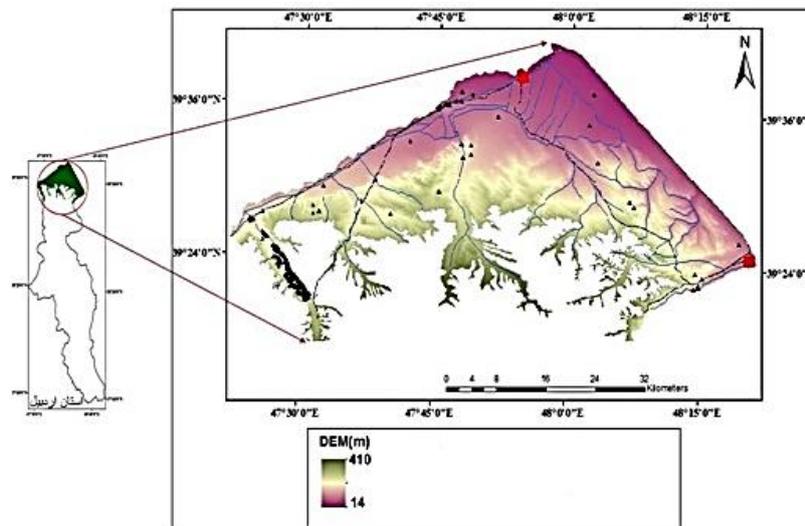


Figure 1: Geographical Location of the Moghan Plain

The most common crops in this region are wheat, barley, maize (three types), and cotton. The present study used the data of the period of 2007-2016 including those on the annual input flow into the Aras dam reservoir, the average annual flow of the dam, the average monthly storage, the average annual water volume, and the average annual water allocation. The demand for water allocation from the Aras dam comes from the drinking sector, downstream lands of agriculture, industrial sector, and the environmental sector. As previously mentioned and according to the data available, the highest amount of water is allocated to the agricultural sector (mainly consumed for irrigation of the downstream regions). Since the number of water requirements was not, consequently, changed in the industrial, drinking, and environmental sectors, the water was allocated to the Aras Dam in the agricultural sector. All data on evaporation and transpiration, the water requirement of cultivated plants as well as conventional farming practices of the region were derived from the Irrigation and Drainage Exploitation Company of the Moghan plain (Figure 2).

Of the total 1202.69 million cubic meters of the input water to the network, 100.24 million cubic meters (equivalent to 8%) is wasted on the main channel and the remaining 1102.24 million cubic meters (92%) is distributed in the network of which 868.18 million cubic meters (72.2% of the total input water) and 234.28 million cubic meters (19.5% of the input water to the network) are distributed among the agricultural sector and gardens and non-agricultural sector, respectively.

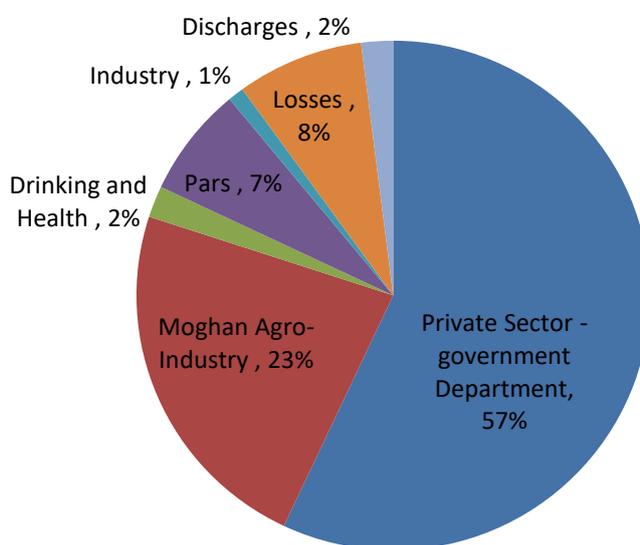


Figure 2: The Contribution of Different Consumption Segments in the Moghan Network (%)

Figures 3 and 4 depict the acreage and stock comparisons of aquaculture in the past five years, respectively, which was increased year by year by the continuous follow-ups of the realization of the company's income arising from the price of water and have the upward trend.

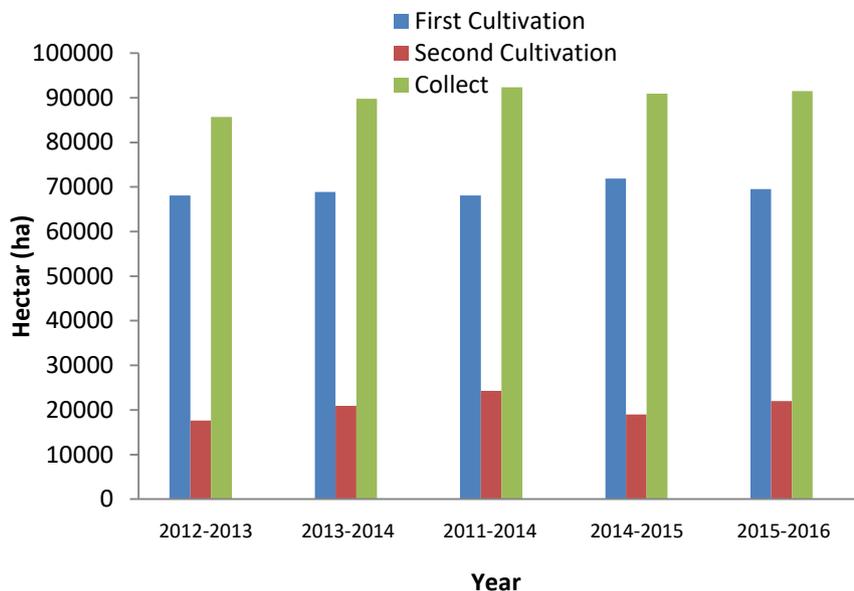


Figure 3: The Network Cultivation Diagram in the Last Five Years

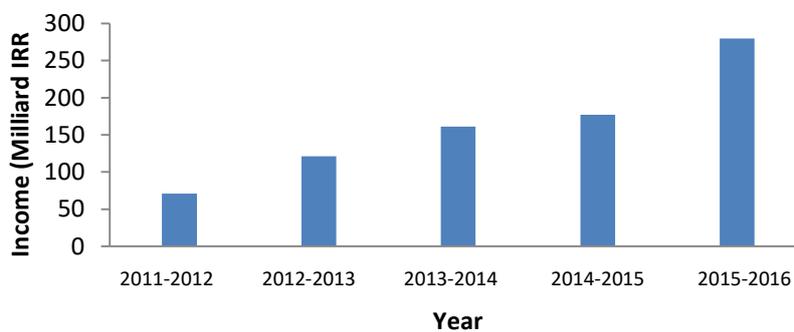


Figure 4: A Collected Comparative Graph of the Price of Water in the Past Five Years

2.2 Optimization Using Artificial Neural Network (ANN)

All optimization problems consist of two stages of modeling and planning including, the formation of the objective function, constraints, and limitations (first stage, modeling) and the determination of the optimal conditions to achieve the ideal solution (second stage, planning). An artificial neural network consists of a set of neurons with internal links with one another, which can provide output responses based on the input data and information. Neural networks are usually created in a layered and regular manner. The first

layer, which the input data are entered, is the input layer. The middle layers of the hidden layers and the last layer, which provides the output responses are the model, is the output layer (Mnhaj, 2000).

The total input set into the neuron is given by Equation 1:

$$\text{net}_j = \sum_{i=1}^n w_{ij}x_i \quad (1)$$

in which, W_{ij} is the intensity of the connection of the neurons, which is determined during the learning process. The next step involves determining the output level of the neuron to the total inputs. The activity function used in this study is the sigmoid function and the network output is between 0 and 1, which is defined as follows:

$$f(s_j) = \frac{1}{1 + e^{-s_j}} \quad (2)$$

The input of data in raw form reduces the speed and accuracy of the model, so the inputs and outputs must be standardized between 0 and 1, hence the data are normalized as equation (3).

$$\begin{cases} Y_i = \frac{X_{oi}}{X_{o\max}}, & X_{oi} \geq 0 \\ Y_i = \frac{X_{oi}}{|X_{o\min}|}, & X_{oi} < 0 \end{cases} \quad (3)$$

in which, Y_i , X_{oi} , $X_{o\min}$ and $X_{o\max}$ are standardized, observation values, minimum observational, and the maximum observational values, respectively.

The processes of the neural network with a return-retarded learning method are shown in Figure4 (Nejatpour, 1999).

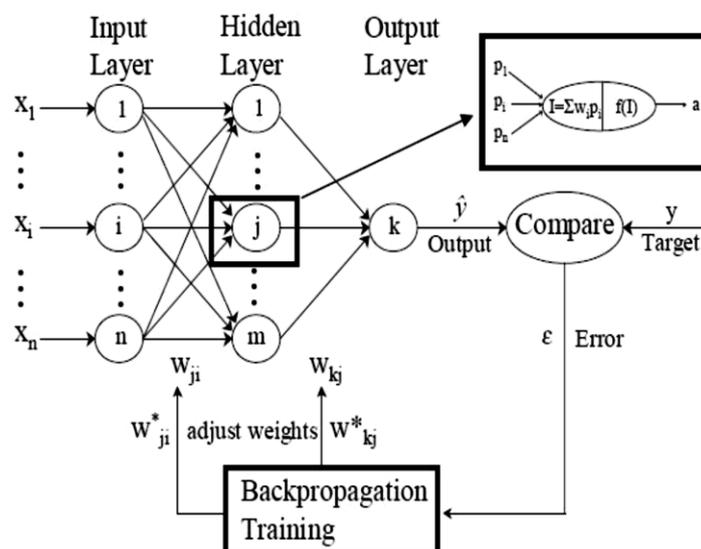


Figure 5: The Three-layer Neural Network with Back-Propagation (BP) Training Algorithm

2.3 Problem Definition

This study aimed at maximizing the gross revenue from the sales of crops as well as minimizing the losses caused by the shortage of water resources allocation in the agricultural sector. Therefore, this study tried to evaluate the artificial neural network method in predicting and presenting optimal water allocation in exploitation months.

2.4 The Objective Function

Since after the beginning of the growing season, the cultivating area and agricultural costs remain constant, the objective function is determined to maximize the gross revenue from sales of crops as well as minimizing the losses caused by shortages in the allocation of drinking costs, industries, etc. Therefore, the objective functions are equations (4) to (6):

$$\text{Maximize: } TB - TCE - TCS \quad (4)$$

$$TB = \sum_{j=1}^4 \sum_{C=1}^8 (Y * A) * P_c \quad (5)$$

$$Y_c = Y \max_c \left(1 - \sum_{t=1}^n ky_{ct} \left(1 - \frac{ET_c}{ET_{\max_c}} \right)_t \right) \quad (6)$$

in which TB , TCS , TCE , Y_{cj} , C , Ac_j , j , $Tmax_c$, c , $kyct$, and $Etmax$ are the net profit of the network, the shortage of expenditures on allocating to the drinking and industrial sectors, the shortage of expenditures on allocating to the environmental sector, the total weight of the produced crop c in area j as per unit area below C , the total cultivated area of the crop c in area j , the unit price of the productive weight of the crop c , maximum production of the crop c without water stress, sensitivity coefficient of the crop c in month t and actual evaporation of the crop c in month t without water stress, respectively. The index c represents the type of the crop, j is the cropping area and t is the time index (month).

2.5 Limitations and Constraints

In the initial state, the storage of the dam is considered to be intact and then the harvesting is reduced.

Drinking water and services are fully provided.

The amount of water should be more than what is needed for products in each area.

The total cultivation area should not exceed the total area and should always be considered constant.

At the end of the year, the storage capacity of the dam should not be less than its initial volume.

The following equations represent the mathematical form of the above constraints and limitations:

$$W_{dem_{jt}} \leq W_{av_{jt}} \quad (7)$$

$$W_{dem_{jt}} \equiv \sum_{c=1}^8 W_{dem_{jt}} \quad (8)$$

$$W_{av_{jt}} = SW_{jt} + GW_{jt} \quad (9)$$

$$GW_{jt} \leq PGW_{jt} \quad (10)$$

$$SW_{jt} = RDR_{jt} + BW_{jt} + Var_{jt} \quad (11)$$

$$BW_{jt} \leq PBW_{jt} \quad (12)$$

In these relations, the water allocated to j area at month t , the water available in j area at month t , the water allocated to product c in j area at month t , the groundwater used in j area at month t .

In these equations, $W_{dem_{jt}}$ represents the water allocated to the area j at month t , $W_{av_{jt}}$ denotes the water available in the area j at month t , $W_{dem_{jt}}$ displays the water allocated to the crop c in the area j at month t , and GW_{jt} shows the groundwater used in the area j at month t .

After defining the constraints, the appropriate options must be chosen for different parts of the neural network model. However, the correct choice of these options will have a direct impact on the performance and speed of this model. In this study, various options were, also, tested to achieve the best solution for each part of the neural network model based on their high capabilities. In some cases, the best option was chosen for each case using the sensitivity analysis.

2.6 Evaluation Indices

Several indices are needed to compare the results of the neural network and the actual values as well as their evaluation, which can judge the function of the model in the whole set of data in comparison with the experimental results. To this end, the correlation coefficient (R2), Mean Absolute Magnitude Error (MAE), and Root Mean Square Error (RMSE) were used. The equations are as follows:

The second power of the linear correlation coefficient, R2, is called “the coefficient of linear correlation determination”, which determines the degree of correlation between two variables (computational and observational data):

$$R^2 = \frac{\sum_1^n (\text{calc} - \text{avg.obs})^2}{\sum_1^n (\text{obs} - \text{avg.obs})^2} \quad (13)$$

B) Squared of square error:

$$\text{RMSE} = \frac{\sqrt{\sum(Q_o - Q_M)}}{N} \quad (14)$$

In these equations:

The mean of observational data, n is the total number of observational and computational data, observational data, computational data corresponding to observational data, and Q_o and

Q_m are the observed (measured) and the predicted parameters, respectively.

The ideal value for R^2 and RMSE is equal to 1 and 1-10%, respectively.

3. Results and Discussion

The study used the monthly statistics for the period of 2008-2017 investigates the ability of the neural network model to perform the analysis using the Neuro-Solution software. Also, according to the literature and the acceptable performance of ANN, the present study applied the artificial neural network method with the Momentum training algorithm. Based on the presented relations and proportions, the distraction data were excluded; thus, the collected data consisted of 1064 data. About 70% and 10% of the data were used to train the network and validate the model, respectively. This pair of data has been selected randomly from all possible historical couples by maintaining continuity of time. The random selection was applied due to the sufficient coverage of training information from all occurrences in the historical time series. Using the validation of the data, the effectiveness of the trained model was examined. After training the network and verifying it, the network would be able to provide new data and provide the appropriate output. Therefore, 20% of the remaining data was used for testing the network.

Since the output parameter was only one parameter for all networks, different networks, which have an output, were considered. It should be noted that the neural network can have three output parameters simultaneously, but in the first trial and error, a neural network was used for each output based on the lower correlation of the time parameter using the same specifications and functions. For the output parameter, the number of suitable cycles was chosen as an attempt to error. These numbers of appropriate cycles were based on the proper training, preventing over-learning, and lack of learning.

3.1 The Results of Training and Testing of Neural Network Model

In this study, 1000 cycles and 3 hidden layers were appropriately considered. The best results for the artificial neural network model are presented in Table 1.

Table 1: The Comparison of Artificial Neural Network Performance

Type of network	Transformation function	Training algorithm	Network training stage		Network testing stage	
			RMSE	R ²	RMSE	R ²
ANN	Sigmoid Axon	momentum	0.038	0.79	33.12	0.88

In Figure 6, the results of artificial neural network implementation and observation values were compared for the water allocated during the growing season of the Moghan plain. It is observed that the results of artificial neural network implementation are very close to the measured amount of water allocation. Therefore, there is high convergence, proficiency, and efficiency in this method in water resources systems.

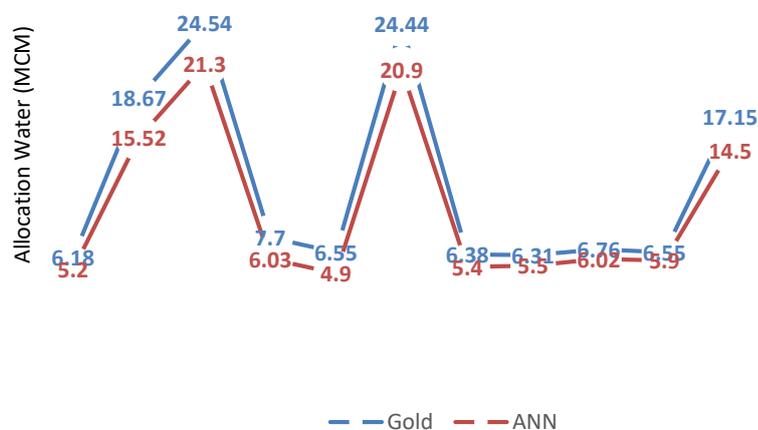


Figure 6: Comparison of Realized Allocated Water and Artificial Neural Network Implementation

According to Figure 7, the total optimal acreage of the crops is equal to 6,953,243 hectares. Given the results, it is concluded that cotton has lower acreage due to its low economic efficiency than other products. Wheat has, therefore, been considered as a high-yielding crop due to its high economic profits. In summary, the economic profitability model should tend towards high-income crops and economic crops in this region.

By examining Figure 7, it is determined that the total optimal cultivating area of the products is equal to 6,953,243 hectares. Given the results, it is concluded that cotton has a less cultivating area due to its low economic efficiency than other products. Wheat has, therefore, been considered as a high-yielding product due to its high economic profits. In sum, therefore, it is necessary that, in this region, the economic profitability model should tend towards crop production obtaining high-income and economic products.

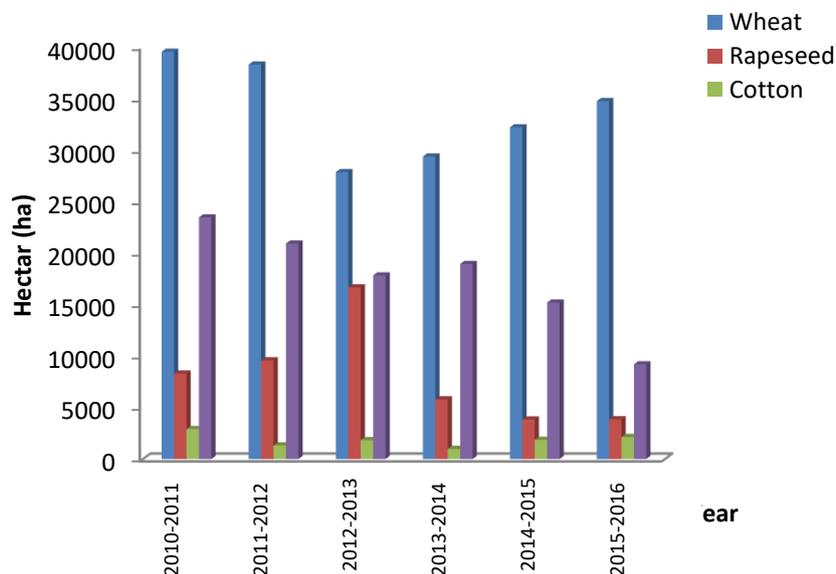


Figure 7: Total Optimal Acreage at the Beginning of Each Month per Hectare, Based on Estimated Values

In Figure 8, net profit is shown each year by applying coefficients of 0.6, 0.75, and 0.9. As shown in Figure 8, the profit experienced a bullish and growing trend during 2008-2010, but then a downside trend. Applying the coefficient of 0.9, compared to the two coefficients of 0.75 and 0.6, includes greater profit from the sale of products. In these years, the lowest amount of profit belongs to 2011, which can be attributed to the optimum acreage area and the regional water allocation. The highest amount of income, therefore, belongs to the years 1997, 2008, and 2009 indicating the regional agricultural growth.

As can be seen in Figure 8 and Table 2, the artificial neural

network along with 1820 million cubic meters per year includes 9% of optimal water resource utilization in the agricultural sector. Generally speaking, due to allocations made by the artificial neural network, \$150 billion of revenues is generated in optimal water resource allocation, which equals 44% of the economic growth in the agricultural sector.

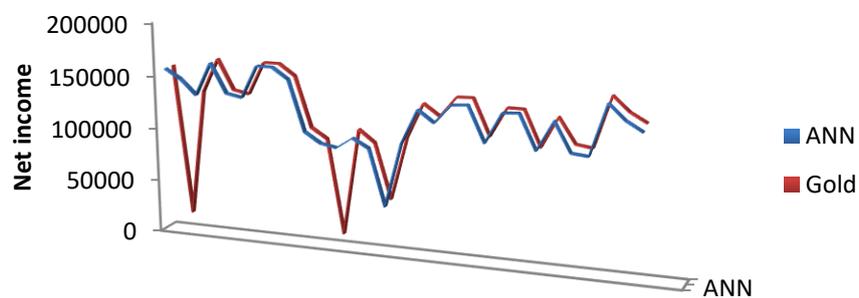


Figure 8: The Net Profit in Each Year by Applying Coefficients of 0.6, 0.75 and 0.9

Table 2: The Economic Comparison of Artificial Neural Network Model in the Agricultural Sector

Economic growth (%)	income (billion IRR)	Water consumption in the optimum state (million m ³)	Water consumption	model
44	150	1820	agriculture	
-	-	-	services	ANN
44	150	1820	total	

3.2 Comparing the Results of This Study with Other Researchers

Comparing with the income (economic growth) of the economic allocation of the regional water resources by Habibi Davijani et al. (2013), this study showed that, in comparison with the central and desert parts of Iran, in the studied area (the Moghan plain), wheat is considered as a high-yielding regional crop due to its high economic profits. As a result, the economic allocation of water resources will have a 44% growth rate in this region.

4. Conclusion

In this study, a new method of the artificial neural network, with 1000 cycles and 3 hidden layers and a correlation coefficient of 90% ($R^2 = 0.95$), was used in network test sector, irrigation and drainage network the Moghan plain to allocate the optimal water resources using an economic approach. The results of the implementation and application of the proposed model were determined using the actual values of the comparison and efficiency of the applied method. The results revealed that the proposed model (artificial neural network) performs well in predicting the water resources values. It has a high speed and accuracy in finding the optimal solution. The neural network allocations were generated \$ 150 billion (44%) in the agricultural sector. It was also concluded that by increasing the number of wheat fields, the income will increase and the economic growth will, finally, be achieved for the Moghan plain.

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